Final Project Report: Real Time Tennis Match Prediction Using Machine Learning

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This project adopts an innovative data model by combining both historical performance data and real-time player in-game stats, and apply machine learning to predict tennis match outcomes. This project explores and compares four data models mixing historical data and real-time stats, while applying various machine learning techniques such as logistic regression, support vector classification (SVC) with linear, RBF and polynomial kernels, and Naive Bayes classification. Feature selection techniques such as recursive feature elimination, and principal component analysis were employed as well. We find that applying SVC with a RBF kernel on historical data alone gives the best prediction. More importantly, a thorough analysis on results was done to reveal and understand the predominant challenge in this data model - high bias, as our collected feature set does not cover edge cases and "comback" situations. **TTL** (total points won) is found to be the most dominant and predictive feature for linear models, with other standout features also revealed. From there, the project outlines the future work needed to combat the high bias issue by proposing other features that could be used but not included in the current project.

1 Introduction

In the 2017 Stuttgart Open, Roger Federer, then an 18-time grand slam champion, lost to the world No. 302 player Tommy Haas on a grass court, which hadn't happened since 2002. Based on past performance alone, almost any model would have predicted a Federer win in pre-game bets. This motivates us to apply machine learning to predict tennis matches in real time; in particular, we want to apply a hybrid model that combines historical and real-time, in-game information.

2 Related Work

Extensive research has been done on tennis as it is an ideal candidate for using hierarchical probability models: a match consists of a sequence of sets, which in turn consist of several games, which in turn consist of a sequence of points. Knottenbelt [5] proposed a common opponent model to extract features between two players that is found to be very predcitve in his stochastic models, while James [3] has done thorough study on probability Formulas and statistical analysis on tennis matches. Recent researchers began to apply machine learning on tennis pre-game predictions based on past performance (including previous encounter, current ranking, etc), such as Sipko [9], and Madurska [6] - whose by-set method inspired us as well.

Our project seeks to apply classification algorithms from machine learning to model men's professional singles matches by using both pre-game, historical performance calcualted via a common opponent model [5], and real-time, in-game stats [4] [6]. As pointed out by Sipko [9], this in-game approach "allows the model to capture the change in a player's performance over the course of the match. For example, different players fatigue during a match in different ways." We hope that results from our predictions can be extended to give real-time coaching advice to support game strategy decision.

3 Dataset and Features

3.1 Dataset & pre-processing

This project employs two open source datasets mainly for labels and features, by Jeff Sackmann [8] and [4]. The *Match Charting Project* contains set level data from 1442 matches, spanning from 1974 to 2017. *Tennis ATP* dataset contains match level data from 1969 to 2017.

- **Pick date range**: Matches from 2000 - 2017 are used as samples (1415 matches) to focus on the comtemporary game of Tennis.
- **Remove duplicates via match id**: Since both datasets are manually entered via crowdsourcing, there are some inaccuracy and duplication that require our pre-processing.
- **Remove Davis Cup**: Davis Cup is the World Cup of tennis, where players play for their country. We decided to remove all Davis Cup entries since group

matches may include strategic moves that are considerably different from individual tournaments.

- **Merge Tennis ATP and Match Charting Project**: Real-time stats are obtained the *Match Charting Project* dataset, whereas historical performance for both players is computed from *Tennis ATP*. Two datasets are merged on player's first and last name, with players of the same names removed manually.
- **Standardize Features** We are unable to extract all features listed in Sipko [9]. While extracting features from *Tennis ATP* was easy, the *Match Charting Project* data proves much more challenging with its detailed stats and file structure. We managed to extract a subset of all possible features from processing the point-by-point data, and standardized across the historical and current features.

3.2 Feature Extraction

Original dataset we used denotes Player 1 as the winner and Player 2 as the loser. While processing, we decide to represent each set in each match with two rows, one from each player's perspective, and label the match result accordingly. Thus we have one row per player per set per match, containing features from historical data and real time data. Historical data includes match details and player's past performance; real-time data, for the scope of this project, will be defined as the performance from all previous sets in the match:

1. A vector of input features ($\mathbf{X}$), describing the performance in previous set and historical performance from one player's perspective
2. A target value ($\mathbf{y}$), indicating the match outcome. $y \in \{1, -1\}$

3.2.1 Symmetric Feature Representation

There are two approaches to represent features from two players. First, we can have two features for the same metric (e.g. $RANK_1$ and $RANK_2$). This approach doubles the number of features, but also provides a quantitative measure that we can compare across all players. Second, we can look at *differences* between two players (e.g. $RANK_{DIFF} = RANK_1 - RANK_2$). This would reduce the number of features, but does not allow the model to compare across players. Previous research has shown that the difference variables are predictive enough [9] [3] for past performance (on match level). For current performance (on set level), we evaluated the performance of both approaches. There was no difference in terms of accuracy, hence the difference model was used for current match as well for consistency.

3.2.2 Common Opponent Model for Past Performance

We use a method proposed by Knottenbelt [5] and extended by Sipko [9] to construct *difference variables* capturing player characteristics and past performance, by using their **common opponents** to achieve a fair comparison. The detailed code can be found in our codebase, while the process works as follows:

- Identify a set of common opponents between the two players of a given match.
- Compute the average performance of both players against the common opponent.
- Take the difference between average performance for each extracted feature.

3.2.3 Edge Cases for Common Opponents

We have run into 2 edge cases: (1) when at least one of the players is new; (2) when two players do not have any common opponents. Upon investigation, our solution is: (1) when the player is new with no historical data, we remove the samples, which consist of 84 data points out of 1421 matches; (2) when two players do not have any common opponents, we compute the average for each player (regardless of opponents) and take the difference, which consist of 74 out of 1421 matches. Note, as described in Section 3.2, our final sample size will contain $2x * 1421$ rows, where x is the number of sets played in each match.

It's worth noting that whenever we encounter NULLs in the feature data, we remove the entire row to avoid the confusion introduced by different null-filling options, and to be consistent and rigorous. This reduces available data points for training and evaluation, and could potentially impact model performance.

3.3 Feature Lists

3.3.1 Features from historical matches

Features are the *difference variables* averaged for both players obtained from a common opponent model [5], unless otherwise noted. They are:

- **Performance Features**: Number of aces, double faults, break points faced and saved; Percentages of winning on first and second serves, and first serve in rate.
- **Match Details**: Match duration, number of serve games, number of serve points per game
- **Player Bio**: ATP Rank, ATP Rank Points, same handedness, height

We also extracted and added two more features to the models after the first pass of the project and diagnostics that reveal high bias as our main hindrance of performance, which we will elaborate further in Section 5. The two added features are **duration win/loss rate** which calculates the average difference in duration (in minutes) of the past matches each player won or lost respectively, using the Common Opponent Model, and **age diff win/loss rate**, which calculates the average age difference of the past matches each player won or lost respectively, using the Common Opponent Model.

3.3.2 Features from current match performance

- **Performance Features** Number of aces, double faults, winners and total points won; Percentage of winning on first and second serve, return points won, first serve in

- **Match Details** Surface (hard, grass, or clay), match type
- **Player Bio** Same handedness

4 Method

4.1 Logistic Regression

As a start, we built a logistic regression on the data using Scikit-Learn's implementation (add citation). The $L2$-penalized model minimizes the cost function below:

$$\min_{w,c} \sum_{i=1}^{n} \log(e^{-y_i(X_i^T w+c)} + 1) + \frac{1}{2} w^T w$$

The solver implemented in the code uses a coordinate descent algorithm, and the detailed proof can be found in Hsieh 2008 [2]

4.2 Support Vector Machine

Next, we used a linear support vector classifier from scikit-learn [7] to predict the tennis match outcome. Given training vectors $x_i \in \mathbb{R}^n$ and the label vector $y = \{1, -1\}$ where 1 represents a win and -1 represents a loss, we can formulate the support vector machine as solving the following primal problem:

$$min_{w,b,\varsigma} \sum_{i=1}^{n} \varsigma_i + \frac{1}{2} w^T w$$

$$s.t. y_i(w^T \theta(x_i) + b) \geq 1 - \varsigma_i, \varsigma_i \geq 0$$

Its dual is

$$\begin{aligned} \min_{\alpha} \frac{1}{2} \alpha^T Q \alpha - e^T \alpha \\ s.t. y^T \alpha = 0 \\ 0 \leq \alpha \leq 1 \end{aligned}$$

where e is the vector of all ones, and $Q_{i,j} = y_i y_j K(x_i, x_j)$, and $K(x_i, x_j)$ is the kernel here. We tried different kernels including linear, RBF, and poly which give similar performances.

4.3 Other algorithms

Moreover, we've implemented **Naive Bayes** as a classifier, to check the model performance. We were curious to test if Naive Bayes classifier works well; and if so, if it indicates that the features are *conditionally independent* - i.e. break point percentage, rank difference, and all other features don't really relate to each other as long as I win the matches. Given a class variable $y = \{1, -1\}$ and a dependent feature vector x_1 through x_n, BayesâĂŹ theorem states the following relationship:

$$P(y|x_1, ..., x_n) = \frac{P(y)P(x_1, ..., x_n|y)}{P(x_1, ..., x_n)}$$

In particular, we have chosen the Gaussian Naive Bayes algorithm following the assumption that X with respect to $y = \{1, -1\}$ is distributed according to a Gaussian distribution. This gives us the feature likelihood as

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2})$$

And we use the following classification rule:

$$\hat{y} = arg \max_y P(y) \Pi_{i=1}^{n} P(x_i|y)$$

We mainly used Naive Bayes to benchmark model performance against logistic regression and linear SVC, as it is extremely fast to run.

5 Experiments, Results, Discussion

We organized discussion around results and experiments in the following 4 questions. We mainly recorded results using logistic regression and linear SVC, for their excellent performances under our various data models. Moreover, cross-validation (10-fold) is done on all the results to ensure robustness. The general random split of train-dev-test (60:20:20) is also observed. We compared different models using the dev set for evaluation; once we had the best model, we passed that through the test set for a final model accuracy score.

5.1 Parameters, Metrics

For logistic regression, we chose L2 regularization with the *liblinear* Algorithm [2] to use in the optimization solver. For small datasets, *liblinear* is shown to perform really well. The penalty function makes sure that we don't overfit. For SVC, we explored multiple options such as linear, poly and RBF based on empirical performance on dev set, and used **RBF** (Gaussian) kernel for historical only data model and **linear** kernel for the rest. In general, we think this choice makes sense as RBF kernels are general purpose and usually the first thing to try when we are not processing text. We also used *squared hinge loss* $(\max(0, -)^2)$ to penalize violated margins more strongly, based on emprical evidence on our particular dataset. Moreover, we used **L2 regularization** as well, as penalizing large weights tends to improve generalization (because it means that no input dimension can have a very large influence on the scores all by itself) and thus avoids overfitting. As evident by results presented below, this is part of our effort to encourage models to prefer smaller and more diffuse weight vectors (to counteract the fact that a very small subset of features account for most predictive power). The classifier is thus "encouraged" to take into account all input dimensions to small amounts rather than a few input dimensions and very strongly, ideally. Lastly, we set the max iteration to 100,000 as SVM may not converge.

We mainly looked at **accuracy** as our success criterion, which calculates how many labels our model predicts correctly out of all the dev/test labels. We used the term "score" interchangeably with accuracy in this report.

5.2 How well can we predict tennis matches?

To evaluate model performance, it's important to note that for linear SVC and logistic regression, we capped the

number of features to 15 - due to the penalty functions in place, we observed that accuracy drops sharply after we exceed 15 features using RFE. This can be clearly seen in Figure 5.1. Our best model, which uses *only* historical with a RBF-kernel SVC predicts with 94.6% accuracy on test set, after being trained using cross-validation on the train set. The detailed performance comparison of each data method on *test* score (with best performing machine learning algorithm, after being trained on the train set) can be seen in Table 5.1. We have also included the detailed dev set accuracy information in the appendix. This is a surprising learning to us: using past performance alone really gives the best prediction. It also suggests that bringing in more data in the form of real-time stats actually worsens the model performance, due partly to the presence of penalty functions. However, once we bring in real-time stats after set 2, we almost have the on-par model performance again (with smaller variance). Interestingly, using real-time info reduces variances, as models built on historical data only show a greater variance compared to models using current data which are more stable.

Figure 5.1: Accuracy vs. Number of Features

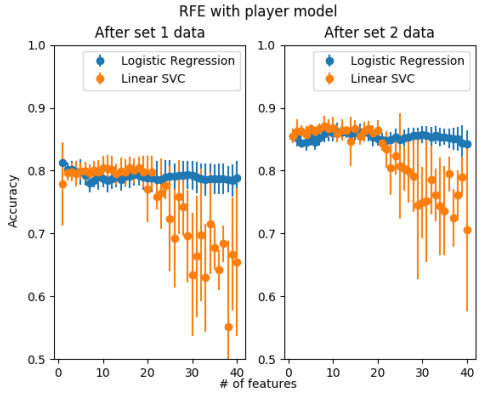


Table 5.1: Different Modeling Method Test Accuracy Comparison

Data Model	Best Performing Algorithm	Accuracy
Historical Data Only	SVC with RBF kernel	86.5%, std.dev = 4.2%
Real-Time Data Only, After Set 1	Logistic Regression, capped at 15 features	79.0%, std.dev = 0%
Historical + Current Data (after Set 1)	Linear SVC, capped at 15 features	80.1%, std.dev = 0.7%
Historical + Current Data (after Set 2)	Linear SVC, capped at 15 features	86.0%, std.dev = 3.7%

5.3 Does using current, real-time info improve accuracy?

No, it does not. We have shown the following confusion matrices to document data model's performance in Tables 5.2, 5.3.

Table 5.2: Historical Only

	TRUE	FALSE
POSITIVE	52.7%	0.1%
NEGATIVE	47.1%	0.1%

Table 5.3: Historical + After Set 2

	TRUE	FALSE
POSITIVE	42.9%	6.3%
NEGATIVE	44.4%	6.4%

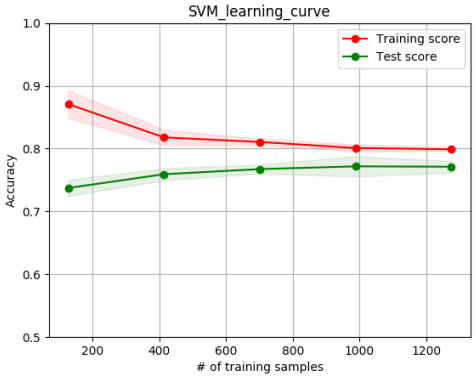
5.4 What features are the most predictive, for linear models?

Using recursive feature elimination across our data models and linear algorithms, we find that **TTL** (total points won), which indicates how many points one player has won in the match up till our cut-off point (either after Set 1 or 2, depending on the run), is the most important feature by a wide margin. Adding more features only leads to minimal improvement at best. In most case, having **TTL** alone almost always yields the best performance. Other top features include: **RCV** (% of return points won) from real-time data, **BPP** (breaking point saving %) if only historical performance data are used as features. Because of suspected collinearity and overfittng, we wanted to make sure we don't consider all features, but really understand how performance changes as we go from the most predictive feature to the least predictive feature. Since we are using logistic regression and linear SVC mainly, we looked at recursive feature elimination to find the optimal number of features (by recursively considering smaller and smaller sets of features). The graphs of how accuracy changes with number of features are included below in Figure 5.1; notice how it drops over time due to L2 regularization present in both algorithms.

5.5 Diagnostics

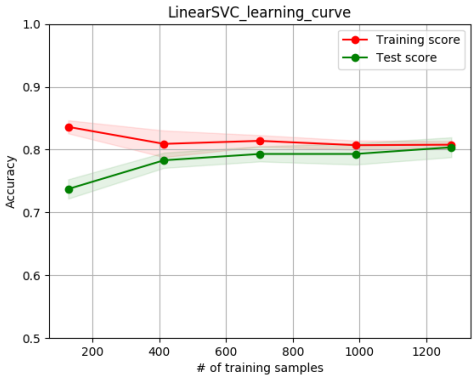
Drilling deep into our model performance, we observed the problem of **high bias** (high training error; Small gap between training and test error) after plotting the learning curves in Figure 5.2 and corroborated by Figure 5.3.

Figure 5.2: SVM Learning Curve



To combat high bias, we turn to unimplemented new features as this is the best solution outlined in Andrew

Figure 5.3: Linear SVC Learning Curve



Ng's error analysis slides. Despite other available features, our models learned that the information contained in other additional features (such as number of double faults or aces, etc.) is mostly already captured by **TTL**. Therefore, we need to find features that are complement to **TTL**, revealing information that could let to a "come back" even if the player is at the moment behind, in order to get a more accurate prediction.

Two features that we added after the poster session for this purpose were:

1. **duration win/loss rate**: calculated as the average difference in duration (in minutes) of the past matches each player won or lost respectively, using the Common Opponent Model. When predicting the result of a new match, we divide the difference by the elapsed time of the match that we are trying to predict.

2. **age diff win/loss rate**: For this feature, we calculate the average age difference of the past matches each player won or lost respectively, using the Common Opponent Model. Then, when predicting a new match, we divide the difference by the age difference between the two players in the match that we are trying to predict.

However, after adding these two features, we realized only the historical data model benefited slightly, with a marginally better accuracy rate achieved using SVC with a RBF kernel. When used with other algorithms, we do not observe any change in performance or top features' relative ranking.

6 Future Work

For future work, there are still unimplemented features that we think will improve the model accuracy, such as: the (relative) importance of tournaments/matches for player, the number of matches a player had in the days before this match (as a proxy for fatigue), the tightness in schedule and intensity of those matches, number of matches the player played before in similar environment (location, weather, surface), time decaying factor, etc. It will also be interesting to see if historical + current data give better performance with updated feature lists.

7 Conclusion

The use of common opponent model and difference variables already offer high predictive power when coupled with SVC with a RBF kernel. And it's insightful to learn that for real-time prediction and linear models, total points won from before can really tell who is more likely to win, and a player's performance when faced with break points directly indicates his chance of winning. We also learnt that when making in-game predictions, historical performance data matter the most for accuracy and in-game stats hardly matter - i.e. most players actually carry some kind of "memory" when playing. Moreover, we showed that high bias is the main issue for tennis prediction models, and any future model should take this into consideration by coming up with creative features derived from detailed point-by-point data for the maximal gain in accuracy.

8 Appendix

8.1 Results: Dev set score for all algorithms

- **Historical data only**: logistic 0.705, linear SVC 0.512, SVC + RBF kernel for 15 features 0.869, SVC + poly kernel for 15 features 0.455, SVC + linear kernel for 15 features 0.583, **SVC + RBF kernel for all features 0.891**, SVC + poly kernel for all features 0.476, SVC + linear kernel for all features 0.470, Naive Bayes with 15 features 0.676, Naive Bayes with all features 0.673

- **Real-time data only**: **logistic 0.786**, linear SVC 0.606, SVC + RBF kernel for 15 features 0.642, SVC + poly kernel for 15 features 0.529, SVC + linear kernel for 15 features 0.663, SVC + RBF kernel for all features 0.642, SVC + poly kernel for all features 0.529, SVC + linear kernel for all features 0.663, Naive Bayes with 15 features 0.786, Naive Bayes with all features 0.786

- **Historical + After 1st set**: logistic 0.790, linear SVC 0.805, SVC + RBF kernel for 15 features 0.776, SVC + poly kernel for 15 features 0.765, **SVC + linear kernel for 15 features 0.805**, SVC + RBF kernel for all features 0.505, SVC + poly kernel for all features 0.587, SVC + linear kernel for all features 0.554, Naive Bayes with 15 features 0.780, Naive Bayes with all features 0.772

- **Historical + After 2nd set**: logistic 0.855, **linear SVC for 15 features 0.860**, SVC + RBF kernel for 15 features 0.789, SVC + poly kernel for 15 features 0.815, SVC + RBF kernel for all features 0.504, SVC + poly kernel for all features 0.454, SVC + linear kernel for all features 0.570, Naive Bayes with 15 features 0.831, Naive Bayes with all features 0.831

9 Contributions

9.1 Yang "Eddie" Chen

- Researched, reviewed and synthesized relevant literature for applicable ideas and the Related Work

section, such as Clarke and Dyte [1] and O'Malley [3] for difference variable, and Knottenbelt [5] for the common opponent model

- Implemented the Common Opponent Model to look up players stats from common opponents
- Generated ATP Match results for labels
- Applied math fomulations from machine learning models & techniques learned from class, namely logistic regression, SVM and Naive Bayes.
- Conducted error analyses along with Yi & Yubo to understand the root cause of our performance curve, and proposing new checks and solutions.
- Typsetted (LaTeX) the project milestone report, contributed mostly in the poster making, and typesetted & synthesized the final report.

9.2 Yubo Tian

- Feature extraction: generated real-time set-level performance data from Sackmann's MCP [4]
- Data labeling: extracted set level match results from player points information from Sackmann's MCP [4]
- Data processing: joined match-general information, historical data and real-time match data; fixed various issues encountered during the process; wrote scripts to generate all data and labels upon one click
- Initial modeling/error analysis: trained logistic regression model on joined data
- Feature analysis and improvement: after initial modeling, analyzed feature selection results and train/dev errors, designed and extracted additional features in an attempt to fix the high bias problem exposed
- Plot and Report: wrote scripts to plot learning curves; contributed to milestone/ final report contents.

9.3 Yi Zhong

- Feature extraction: get match details related features from MatchChartingProject,
- Data processing: Joined data by linking real-time match data from MCP [4] to match details data from ATPMatches [8] (methods: playerID, playerName etc) (with Yubo).
- Modeling: Wrote the script for logistic, SVC and other model exploration for different data model
- Error analysis: Wrote the graph script for recursive feature elimination, confusion matrix, feature ranking

References

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